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Wavelet Transform use for P300 Signal Clustering by Self-Organizing Map

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Abstract— The Event-Relational Potential (ERP) signals are non-stationary in nature. To extract the informative features from P300 signals, the wavelet analysis is the best analysis tool. This paper investigates development phases, merits and demerits of various existing P300 based Brain Computer Interface (BCI) system. It appraises limitations of wavelet based BCI systems and compares the various wavelet methods for P300 signals. Some of the limitations motivated us to propose a novel method for discovering knowledge embedded in P300 signals using Self-Organizing Maps. The self-organizing feature utilizes to model the data and produce 'clusters' vectors. The discovered knowledge can be used to classify an unknown signal into a signal class. This work aims to interpret EEG signals and utilize it as a device control signal.

Index Terms— Brain-Computer Interface (BCI) system, Encephalogram (EEG), Event-Relational Potential (ERP), Knowledge Discovery, P300 Signals,Self-organizing maps (SOM), Wavelet.

1 Introduction

PAST few years, have witnessed worthy research in non-invasive electroencephalography (EEG) based BCI systems for assisting unblessed people. The research also includes multi-task control applications like wearable applications for able-bodied people [1] [2]. Now days, BCI system development is also gaining attention in the media and gaming industry. BCI systems in principle would directly infer the intensions, brain signals, of subjects under study to infer and perform respective tasks. This involves the discrimination of different neuro-physiological signals and mapping of these signals to movements or actions [3]. For such applications, the P300 signals are widely used in conjunction with brain-computer interface (BCI) systems [4]. The P300 is an endogenous event related potential (ERP) signal, retrieved from parietal lobe (upper backside of head) of the brain. The occurrence of P300 depends on the presentation of stimulus. A typical P300 signal is attained by presenting uncommon target stimulus to the subject that is entrenched in sequence of non-target stimulus. Therefore, the occurrence of P300 signal is directly proportional to the infrequency of target stimulus. The most commonly used patterns of stimulus are visual and audio. The P300 is a positive ERP signal with a latency of about 300ms. The advantage of P300 signal is it occurs suddenly or unintentionally so no training is required. The prominent and erotic content based signal leads to an excellent P300 signal. It is cue-based signal means the subject just need to concentrate on one out of several stimuli [4]. This requires the extraction of several characteristics/ patterns from P300 signals. The wavelet transform is the beast analysis tool for non-stationary brain signals [5]. This paper explores the various pre-existing P300 based BCI systems and briefly discusses the wavelet analysis for P300 based BCI systems. Discovering unknown patterns in an ERP (EEG) signal, i.e. P300 signal is a challenging task. This paper discusses the use of unsupervised approach in discovery of knowledge embedded in P300 EEG signals. On providing unknown patterns of signals the classification can be achieved using various methods like Linear Support Vector Machine (LSVM), Gaussian Support Vector Machine (RSVM), Neural Network (NN), Fisher Linear Discriminant (FLD), and Kernel Fisher Discriminant (KFD) [6] [7] [8] [9]. The paper emphasis on the use of classifier ensemble to embrace the issue of signal responses variability during classification of EEG signals as discussed in [10].

The paper is organized as: The thorough study of various applications of P300 signal based BCI systems in thought recognition has discussed in Section 2. This section also mentions the advantages and disadvantages of P300 based BCI systems. Section 3 discusses the need of knowledge discovery for P300 based knowledge discovery system. Section 4 explains a Novel Approach for Knowledge Discovery using P300 Signals for BCI Systems. Finally, the conclusion is given in Section 5.

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2 Applications of P300 based BCI System

P300 is a positive peak signal that occurs approximately 300 ms after a meaningful stimulus. A typical P300 signal is attained by presenting uncommon target stimulus to the subject

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Table 1: P300 based BCI Systems

S. No.	Data Sets	Pre-processing	Feature Extraction Method	Classifier	Work Done	Result	Advantages	Disadvantages	Year	Ref
1	Dataset from BCI 2003 competition	Band-pass digital filtering (0.5-30 Hz) and normalized to an interval of [-1 1]	the value of samples of filtered data as feature, PCA	Linear Support Vector Machine (LSVM), Gaussian Support Vector Machine (RSVM), Neural Network (NN), Fisher Linear Discriminant (FLD), and Kernel Fisher Discriminant (KFD)	The performance of five classifiers in P300 speller paradigm are compared & shown that the efficiency of using Principal Component Analysis (PCA) for feature reduction results in decreasing the time for the classification and increasing the accuracy	In comparison to winners of BCI 2003 competition which achieved the 100% accuracy after five trails, here FLD + PCA approach yielded prefect performance after four trials.	In FLD method,only 10 channels to achieved 100% accuracy	Speed and cost of the system is directly propostional to the number of channels. As the number of channel increases both the parameters increases.	2006	[12]
2	BCI Competition 2003 data set IIb	with almost no preprocessing	Genetic Algorithm -- features are encoded in variable-length chromosomes, where each gene encodes one feature	Logistic Classifier	In this paper we face the issue of feature extraction by using a genetic algorithm able to retrieve the relevant aspects of the signal to be classified in an automatic fashion	achieved 100% correct letters, yet they are very different	features extracted to be used for the classification of P300 epochs, with almost no preprocessing, The GA deals not only with features, it optimizes the features for the classifier used in the fitness function as well.	More the number of feature extractors, the bigger the search space is required	2008	[13]
3	Data set IIb (P300 speller paradigm) which is obtained from the BCI competition 2003 data bank	sampled at 240Hz	ICA	simple classification method	PERFORMANCE ANALYSIS OF A P300 BCI SPELLER THROUGH SINGLE CHANNEL ICA	Accuracy of 96.8% is acieved	Automatic extraction method avoids the selection step and performs substantially faster than the manual selection method. Also the appropriate number of averages improves the SNR of P300 patterns which lead to a better classification than in an equivalent non-ICA method	Only one recording channel is available, the results are not as favourable as those in the multi-channel applications.	2008	[14]
4	10 electrodes were applied to the scalp according to the international 10 20 system at the locations Fz, Cz, Pz, Oz, C3, C4, P3, P4, PO7 and PO8 and referenced to both ear lobes.	sampled at 256 Hz using the EEG amplifier Mindset24 by Nolan Computer Systems LLC.	PCA	Fisher's Linear Discriminant Analysis (FLDA)	developed a BCI based on the P300 event-related potential as a device for game control	Classification Accuracy Accuracy 84.9%	the game is controlled without any motor actions	Showing true neurofeedback effects requires long-term studies with multiple subjects and multiple sessions and is beyond the scope of this work	2009	[8]

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S. No.	Data Sets	Pre-processing	Feature Extraction Method	Classifier	Work Done	Result	Advantages	Disadvantages	Year	Ref
5	Cz, CPz, P1, Pz, P2, PO3, POz, PO4, according to international 10–20 system	sampling frequency of 1000Hz	Features based on downsampled signals, Continuous Wavelet Transform, and the Common Spatial Pattern technique	Least-Squares Support Vector Machine	implementation of a feature extraction procedure on a new ultra low-power 8-channel wireless EEG device	subjects are potentially able to communicate a character in less than ten seconds with an accuracy of 94.5%, which is more than twice as fast as the state of the art	a subject can spell words more than twice as fast as the current state of the art	the tuning of the LSSVM classifier is very time consuming and does not allow the test session to start immediately after the recording of the training data, which could be a problem for patients	2009	[15]
6	commercial gTec EEG system (an EEG cap, 16 electrodes and a gUSBamp amplifier) connected via USB to the onboard computer	data were filtered using the moving average technique and decimated by a factor of 16.	PCA	Step Wise Linear Discriminant Analysis (SWLDA)	describes a new brain-actuated wheelchair concept that relies on a synchronous P300 brain-computer interface integrated with an autonomous navigation system	accuracy of the brain-computer interface is above 94%	the navigation system successfully solved all the navigation missions without collisions in environments with different conditions and constraints, with the synchronous operation, the user has to be continuously concentrated in the task	One of the main difficulties of current navigation systems is to avoid the obstacles with safety margins and to drive the vehicle between close obstacles	2009	[16]
7	Signals were recorded from 12 Ag/Cl electrodes at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz of the international extended 10-20 standard system with a g.tec cap.	Signals were sampled at 256 Hz, and filtered by a 0.1-30 Hz bandpass filter and a 50 Hz notch filter.	twelve input channels are transformed into two high SNR (signal-to-noise ratio) projections for P300 & μ and β band powers as features for left imagery vs. right imagery and imagery vs. rest	na¨ıve Bayes classifier (NB) for P300 & two-class Fisher linear discriminant (FLD) for motor imagery	The BCI-Tetris is being developed to be tested in pilot experiments with children with attention-deficit and hyperactivity disorder (ADHD).	Online Classification accuracy for P300 is 100% & for motor imagery is 62.5% After the selection of 16 Tetris pieces using different number of repetitions.	In Tetric V1, there is a high spatial variability of the P300 signal, and therefore the classification is not significantly improved by the C-FMS spatial filter.	the control of sensorimotor rhythms require training.	2011	[17]
8	The T3, T4 channel is used for detecting horizontal EOG and vertical EOG? other 14 leads put on the subject? s head according to the standard 10-20 leads for EEG signal measuring	principal component analysis (PCA) is used for reducing the dimension of EEG signal, independent component analysis (ICA) is used for removing EOG artifact	AR model and FastICA algorithm	—	A method based on AR model and FastICA algorithm for P300 feature extracting is presented	Efficiency in removing EOG 93.75%	coherent averaging has some advantages like easy and mobility in P300 signal extracting	choosing 0.5 as threshold produces a better effect, but some useful information is lost if the threshold is too low. Also the most disadvantage of coherent averaging is it needs long time to increase the SNR to a discernible degree for future using.	2009	[18]

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S.No.	Data Sets	Pre-processing	Feature Extraction Method	Classifier	Work Done	Result	Advantages	Disadvantages	Year	Ref
9	considered channels Fz, Cz, Pz, PO7, PO8, OZ, P3 and P4	low-pass filtered with cut-off frequency at 25 Hz, downsampled to 50 Hz	Canonical Correlation Analysis	Linear Discriminant Analysis	proposed a new design for the P300-based BCI, in order to reduce the calibration time of the system	design can reach good P300 detection performances while using much less training examples than current approaches, hence effectively reducing the calibration time	detecting the P300 in "single-trial", i.e., without averaging and reduce the calibration time as it needs only a few training characters to reach high performances	used much less training examples (about 3 or 5 training characters)	2009	[19]
10	BCI competition III data set II	filtered with an 8 order bandpass Chebychev Type I Filter with 0.1 Hz low cutoff frequency and 20 Hz high cutoff frequency	extracted all data samples between 0 and 667 ms posterior of each intensification, assuming that this period will definitely cover the P300 component	Weighted ensemble of SVM, Channel selection with optimized SVM's, Row and column based SVM ensemble	To achieve strong classification with a minimum error rate, an ensemble of SVMs for the classification phase is implemented.	the weighted ensemble of SVM introduces enhancement to the average classification performance of the problem	the weighted ensemble of SVM introduces enhancement to the average classification performance of the problem	weighted ensemble of SVM does not perform its decision blindly	2010	[7]
11	8 out of 32 channels (i.e., Fz, Cz, Pz, Oz, P7, P3, P4, and P8) placed at the standard positions described in the 10-20 International System	6th-order band-pass lter (BPF) & the signal was down-sampled from 2048 Hz to 32 Hz	AR model	adaptive neural network classi er (ANNC)	a new adaptive neural network classi er (ANNC) of EEG-P300 signals from mental activities is proposed.	A 100% average classi cation accuracy was achieved after four blocks for disabled subjects.	an AR model accelerates the training processes, in which the convergence of the tracking error to a small value around zero is faster	to obtain a good classi cation accuracy and transfer rate, the given stimulus must be inputted randomly with no subsequent target i.e. two targets should not be ashed sequentially	2012	[20]

that is entrenched in sequence of non-target stimulus as shown in Fig 1 where N1, N2 and P1, P2 are negative and positive components. Here N1, P2 and N2 proceed the P3 [3]. The occurrence of P300 signal can be easily illustrated using the oddball concept [3]. Here, the user is asked to observe a random sequence of two types of stimuli: one that appears frequently, known as target or oddball stimulus and other is non-target stimulus or normal stimulus. Several researchers have experimented with BCI systems based on the P300 signal. Some of the considerable ones are listed in Table 1 below. This section discusses the advantages and disadvantages of existing P300 based BCI systems. The accuracy of these BCI systems has reported from 84.9 % to 100%.

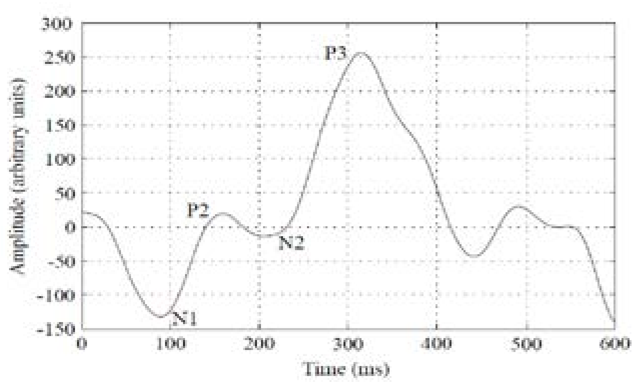

Fig 1. A Typical P300 Wave [3]

However, with such 100% accuracy, these BCI systems are limited by various factors like the number of channels used, the number of feature extractors, tuning of classifiers etc. This section concludes that the P300 signal is capable for the applications like speller device, wheelchair control, environmental control, multimedia etc, which are controlled with the help of a BCI system. The P300 speller paradigm has been a benchmark for P300 BCI systems [11]. This motivates us to develop a BCI system based on P300 signals that will remove the limitations of the previous BCI systems.

3 NEED OF KNOWLEDGE DISCOVERY

The P300 signal pattern can describe by specifying the set of time domain features, frequency domain features and time-frequency domain features. Due to the transient nature of P300 signal, time-frequency features are suitable [21].

Table 2: Wavelets for P300 based BCI Systems

S.No.	Use of Wavelet Method	Research	Year	Ref
1	Quadratic B-spline wavelet transform	To analyze the functional components of P300 ERP	1998	[23]
2	Quadratic B-spline wavelet transform	Deception Detection	2006	[24]
3	Daubechies wavelet	To analyze the functional components of P300 ERP	2006	[22]
3	Kalman filtering and Daubechies-4	P300 detection	2007	[25]
4	Down sampled signals, CWT and Common Spatial Pattern	Mind Speller	2009	[15]
5	db4, bior2.4, bior4.4, bior5.5, coif2, sym4, and sym6	Recognizing and Classifying P300 signals	2009	[26]
6	Quadratic B-Spline functions	P300-based Guilty Knowledge Test (GKT)	2009	[27]
7	Discrete wavelet transforms (DWT)	Detection of P-300 rhythm	2010	[28]
8	Wavelet Transforms (WT)	P300 Feature Detection	2010	[29]
9	Morlet wavelet	Analysis of event-related alpha oscillations in auditory P300	2011	[30]
10	Daubechies-4 wavelet	A P-300 rhythm detection system	2011	[31]
11	Daubechies-4 wavelet	P300 Feature Detection	2012	[21]

To obtain such features the wavelet transform is the best signal analysis tool.

Table 3: EEG Clustering using SOM

S No	Feature Extraction	Features	Classes	Research Work	Year	Ref
1	Kalman filter coefficients	The 10 Kalman filter coefficients were averaged over one second segments (128 samples) of EEG. Coefficient averages were then treated as 10- dimensional feature vectors	Wakefulness ,dreaming and deep sleep were assembled to represent the 3 processes W, R and S respectively.	EEG analysis using self-organization	1991	[33]
2	DFT and DWT	harmonic and Daubechies wavelets components of order 4 (D4) and 16 (D16)	Four Classes: A,B,C and D (Each class is characterized by the variation of signal features distances from a typical class element)	Wavelet transform use for signal classification by self-organizing neural networks	1995	[34]
3	FFT and WT	For FFT features are Power spectrum of each vector with 5 butter-worth filter (delta, theta, alpha, beta, gamma) For WT data filtered using band-pass filters that compute averages for combined wavelet components.	Each cluster is interpreted as the temporary brain function of one test person at different time instances.	Classification of Human Brain Waves using Self-Organizing Maps	1996	[35]
4	WT	Wavelet based features (averaged coefficients and zero crossings)	Three Classes: Normal, Meningioma,Glioma	Automated Classification of EEG signals in brain tumor diagnostics	2000	[36]
5	DFT and DWT	harmonic and Daubechies wavelets components of order 4 (db4)	Signal segments classification into four classes (assumed) using two features resulting from a chosen signal segments analysis	Feature analysis of EEG signals using SOM	2005	[37]

The wavelet features that are short-lived in a signal are detected and extracted, using various methods like Daubechies 4 wavelet, Kalman filtering, Quadratic B-spline etc, to form feature vectors for classification purposes as listed in Table 2. Based on the study, the Daubechies 4 wavelet have outperform with an accuracy of 97.5 % compared to other techniques. The Daubechies 4 wavelet decomposes the signal at different frequency bands, with different temporal resolution [22]. This section concludes that the wavelet analysis can effectively used to extract the joint time-frequency P300 features in the proposed method. Moreover, the wavelet transform also helps in removing the noisy and non-meaningful information from ERP signals. Therefore, it is clear that for ERPs particularly P300, wavelet analysis is a successful feature extraction method [10]. Based on the features extracted, various data mining techniques like classification or clustering are applied. These techniques are extremely helpful for larger input space and feature vector levels are different from each other [32]. The supervised approach fails when there is huge amount of input data as it is not possible to label all input data. Therefore, minimum number of training data sets is chosen. This makes the tuning of the classifiers difficult due to the need of more training sets.

This problem may limit the applications of supervised learning in EEG data analysis. To overcome this limitation, unsupervised learning like Self-Organizing Maps (SOM), is preferred, which discovers the meaningful structure in a raw data [21]. The [33]-[37] have briefly discussed the Self-Organizing Maps (SOM). This paper reports the research work using Self-Organizing Maps (SOM) that have been used along with wavelet transform as feature extraction method for processing EEG signals as depicted in Table 3. The authors have selected and defined adhoc features and assumed the Clusters or Classes. The variations of such paradigm are too high. Therefore, all are intuitive. The next section proposes a method that discovers the features embedded in P300 (EEG) signals, using an unsupervised learning: Self-Organizing Maps (SOM) and wavelet transform.

4 METHODOLOGY

As mentioned, earlier the aim of this paper is to present the framework for the discovery of features of P300 signals using Self-Organizing Maps (SOM) and wavelet transform. The method involves P300 signal processing, feature extraction from the processed signals, discovering signal clusters, classification and interpretation of unknown signals as depicted in Fig 2.

The research methodology involves following steps:

1. P300 Data Sets
2. Signal Preprocessing
3. Feature Extraction
4. Knowledge Discovery using SOM
5. Classification using Classifier Ensemble
6. Command Generation

Mostly the 10-20 international system is used to acquire the EEG signals. The survey of signal acquisition for BCI systems using 10-20 international system have discussed in [38]. The international standard datasets are available online from BCI Competitions. The collected datasets are pre-processed that includes amplification, filtering, digitization etc. As discussed the P300 signals are non-stationary and self-generated signals, for their better interpretation in time-frequency domain, wavelet Transform (WT) is a good analysis tool. Then the Self-Organizing Maps (SOM) is applied to produce the clusters from wavelet feature vectors. This step leads to the process of discovering new patterns from large data sets. Every detected class depicted as a cluster on the map. On providing unknown samples the system can learn and train itself. For the classification purpose, a variety of classifiers like artificial neural network, Back-propagation Neural Network, Hidden Markov Model (HMM), Bayes Network etc have been used [32]. The combining classifiers are used to solve the problem of reducing variance as unstable classifiers can have universally low bias and high variance.

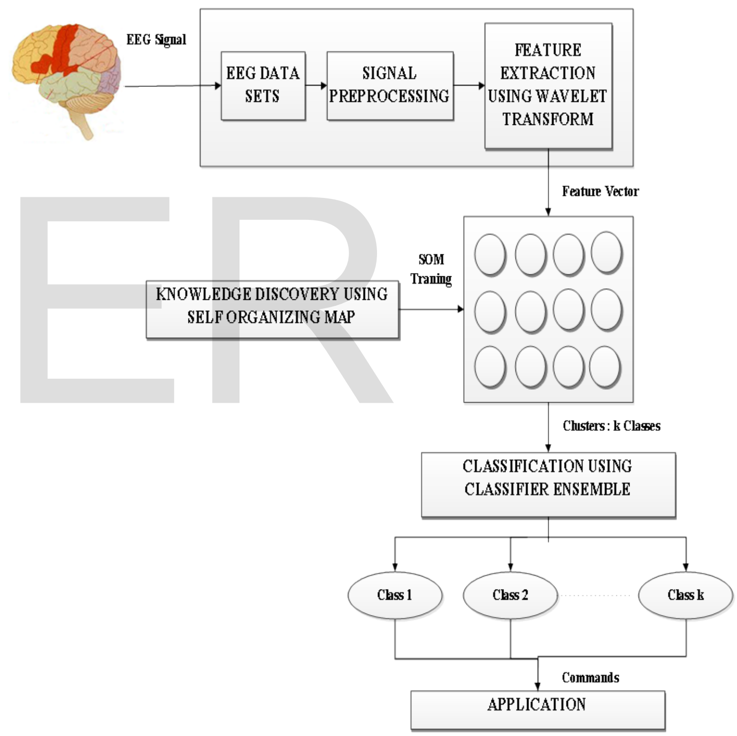

Fig 2. Model

There exist various ensemble-learning methods, commonly used are Bagging, Boosting, Stacking and Voting. Thus, for obtaining a better classification various ensemble-learning methods, commonly used are Bagging, Boosting, Stacking and Voting can be used. The implementation of development phases and testing is under process. These classified signals then will map to device (a standard command file) control command.

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5 Conclusion

The novel way of discovering the knowledge embedded in P300 signals is to classify an unknown signal into a discovered signal class that the said system will interpret into a device control signal. The paper investigates various existing P300 based Brain computer Interface Systems. It also evaluates the P300-based BCI systems using wavelet transform as feature extraction method. The implementation and testing of this BCI system is under progress. The future work focuses to analyze execution results. The developed P300 based BCI system will assist able-bodied and disabled people.

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